Transportation Research Part D 67 (2019) 565–575

Contents lists available at ScienceDirect

Transportation Research Part D

journal homepage: www.elsevier.com/locate/trd

Built environment effects on fuel consumption of driving to work: Insights from on-board diagnostics data of personal vehicles

Wanjing Zhu[a], Chuan Ding[a,b], Xinyu Cao[b,*]

[a] School of Transportation Science and Engineering, Beijing Key Laboratory for Cooperative Vehicle Infrastructure System and Safety Control, Beihang University, Beijing 100191, China

[b] Beijing Advanced Innovation Center for Big Data and Brain Computing, Beihang University, Beijing 100191, China

ARTICLE INFO

Keywords:
Land use
Naturalistic driving
Carbon emissions
Fuel use
Job-housing balance

ABSTRACT

Concerns over climate change and peak oil motivate examining the relationship between the built environment (BE) and individual fuel consumption. Most studies overlook BE characteristics at workplace locations. They often estimate fuel use based on travel distance instead of on actual consumption. This practice ignores other influential mechanisms. This study uses the naturalistic driving data of 660 personal vehicles in Beijing. We apply a structural equations model to examine multiple mechanisms under which the residential and workplace BE affects fuel consumption directly and indirectly through driving distance, travel speed, and driver behavior, controlling for the effect of the street environment along the commute route. We found that all three mediating variables are associated with vehicular fuel consumption for the commute. The workplace BE has the more important effect on fuel consumption than the residential BE, particularly regarding the distance from the workplace to the city center. This study highlights the role of job-housing balance in commuting fuel consumption reduction.

1. Introduction

Fossil fuel consumption leads to air pollution and greenhouse gas (GHG) emissions, which produce enormous challenges at both global and local scales. Furthermore, some scholars predict and debate peak oil (Aleklett, 2012). Although they have differing opinions on the timing of peak production, fossil fuel supply eventually declines since it is not renewable. This is an important issue as sustainable transportation needs to consider fuel consumption of future generations. The rapidly growing fuel consumption in developing countries accelerates the trend. For example, oil consumption in China reached 12.4 million barrels per day in 2016, almost tripling consumption in 1998 (Statista, 2018). As urbanization and motorization in China gradually catch up with developed countries, its oil consumption will continue to grow. Because transportation is a major source of fuel consumption, many urban planning scholars advocate using land use policies such as job-housing balance and compact development to reduce driving distance, fuel consumption, and associated GHG emissions (e.g., Ewing et al., 2015; Nelson, 2017; TaNa et al., 2017; Wang and Zhou, 2017). Compared to driving distance and carbon emission studies, only a limited number of studies focus on the relationship between the built environment and fuel consumption.

Applying the structural equations modeling (SEM) approach on naturalistic driving data in Beijing, this study examines the influences of the built environment at both residential and workplace locations on the fuel consumption of driving commute, through its influence on driving distance, travel speed, and driver behavior (acceleration and deceleration). It answers the following research

* Corresponding author.
E-mail addresses: wjzhu@buaa.edu.cn (W. Zhu), cding@buaa.edu.cn (C. Ding), cao@umn.edu (X. Cao).

https://doi.org/10.1016/j.trd.2019.01.013

Available online 19 January 2019
1361-9209/

questions: (1) Which built environment of residential locations and job locations is more important in affecting fuel consumption? (2) How does the built environment affect fuel usage? (3) To what extent does driver behavior and travel speed moderate the effect of commute distance?

This study collectively contributes threefold to the literature. First, it examines multiple mechanisms under which the built environment affects fuel consumption by including three mediating variables: driving distance, travel speed, and driver behavior, in addition to its direct influence on oil consumption. It offers a more holistic illustration on the relationship between the built environment and fuel consumption. Second, this study moves beyond the built environment at residential locations to incorporate the workplace built environment, as well as control for the street environment along the commute route. Thereby, it minimizes omitted variable bias and offers planning implications for employment locations. This study concludes that the workplace built environment has the more important influence on fuel consumption than residences. Third, fuel consumption in this study is dynamic real time data, instead of estimated or self-reported fuel usage commonly used in the literature. Thereby, the information on fuel consumption is more accurate. Studies using this type of data are scarce in the literature.

This paper is organized as follows. Section 2 reviews the literature on the connection between the built environment and fuel consumption. Section 3 describes the data, variables, and modeling approach. Section 4 presents the model results. The final section summarizes the key findings and discusses policy implications.

2. Literature review

Because of the negative consequences (such as congestion and carbon emissions) of driving, the relationship between the built environment and driving distance, a proxy for travel-related fuel consumption, is a heated literature topic (Ewing and Cervero, 2010; Stevens, 2017). Driving distance is affected by the five "D"s of the built environment: density, diversity, design, destination accessibility, and distance to transit (Ewing and Cervero, 2010). Many recent studies have also focused on the impact of the built environment on travel-related carbon emissions (e.g., Cao and Yang, 2017; Lee and Lee, 2014; Xiao et al., 2017). There are fewer studies on fuel usage, however.

When exploring built environment effects on travel-related fuel consumption, many studies focus on only one driving behavior dimension—distance. Fuel consumption is affected by many factors. From the perspective of planners, fuel consumption depends on travel distance, driver behavior, and road conditions, all of which are associated with the built environment. It is well known that driving distance is influenced by the built environment. Built environment characteristics also affect driver behavior. For example, using a dataset of driving patterns, Brundell-Freij and Ericsson (2005) found that the type of neighborhood and intersection density are associated with average driving speed and acceleration. Road conditions, particularly vehicle density, influence driving speed and hence fuel consumption. During peak hours, vehicle density is generally higher at the central city (characterized by high population/job density) than at suburban locations. Therefore, suburban locations produce a more fuel-efficient speed than the central city. Accordingly, dense development appears to influence fuel consumption in opposite directions. It reduces driving distance as trip destinations are nearby, but increases fuel usage because of low operating speeds. To fully illustrate the mechanism of the built environment on fuel consumption, we consider simultaneously its influence on driving distance, driver behavior, and driving speed.

A few studies find that the built environment influences travel-related fuel consumption through multiple channels. Brownstone and Golob (2009) developed a SEM to estimate the influence of dwelling density on auto use and fuel consumption in California. Their model shows that density is negatively associated with household mileage. After controlling for demographics and household mileage, they found that density also has a negative association with fuel usage. Therefore, driving distance cannot fully capture the variation in fuel consumption. They inferred that other mechanisms are at work; for example, households in denser areas adopt more fuel-efficient vehicles. Using the data in the Baltimore metropolitan area, Liu and Shen (2011) assumed that urban form characteristics influence fuel use through their impacts on vehicle type choice, mode choice, speed, and driving distance. The SEM results show that density affects vehicle type choice, which has an effect on fuel consumption. Furthermore, density is negatively associated with travel speed and indirectly associated with driving distance and fuel use. That is, the effect of density on fuel consumption is through three mediating factors: vehicle type, speed, and driving distance. Ding et al. (2017a) also examined the mediating effect of these three variables in the relationship between the built environment and fuel consumption using SEM. Collectively, these studies suggest that the built environment affects fuel usage by influencing driving distance, vehicle type choice, and vehicle operating speed. However, the studies employing SEM often do not allow built environment variables to influence fuel consumption directly in their conceptual framework, but specify the effect of the built environment on fuel consumption through mediating variables such as driving distance and operating speed (for instance, Ding et al., 2017a; Liu and Shen, 2011; Wang et al., 2014). Because they limit their analysis within the assumed indirect effects, they overlook other unobserved mechanisms, which can be captured through the direct effect. Therefore, scholars should explore both direct and indirect influences of the built environment on fuel consumption.

Another shortcoming of previous studies is that they emphasize the built environment in residential areas. The literature shows that built environment characteristics at trip destinations and along the trip route also influence travel choices (Appleyard, 2012; Tian, 2017). For instance, the built environment at workplace locations is associated with commute mode choice and commute distance (Sun et al., 2017) and the workplace built environment may have a more important impact than the residential built environment (Ding et al., 2014). Therefore, examining only the residential built environment is likely to miss important built environment variables at other places.

When examining the relationship between the built environment and vehicular fuel consumption, previous studies often use self-reported or estimated consumption, instead of naturalistic data. Some studies analyzed annual household fuel usage reported by the respondents (Su, 2011), and others collected travel distances by travel mode and converted them into total travel fuel consumption

(Jiang et al., 2015; Maharjan et al., 2018). Brownstone and Golob (2009) used annual fuel consumption estimated based on odometer readings and adjusted for vehicle characteristics, seasonal variations, and so on. Although Brownstone and Golob employed more accurate fuel consumption data than previous studies, the measure of fuel usage is an estimate. It is desirable to use actual fuel consumption in naturalistic driving, which is scarce in the literature. Wang et al. (2014) is an exception: they used real-time fuel consumption and driving distance of 108 drivers in Southeast Michigan to examine the effect of the street environment on fuel efficiency. However, to illustrate the holistic impacts of built environment variables on fuel consumption, total consumption is a better measure than fuel efficiency. For example, Wang et al. found that employment density reduces average speed and fuel efficiency. This finding is only part of the story since the literature suggests that density also lowers trip distance (Ewing and Cervero, 2010; Stevens, 2017). Although density reduces fuel efficiency, its impact on driving distance might outweigh its influence on fuel efficiency, depending on its relative influences on fuel efficiency and driving distance.

While previous studies explore the influence of built environment attributes on travel fuel consumption, most focus on the built environment at residential locations, overlooking the effect at destinations. This limitation hinders the capacity to inform urban planning at the end of a trip, particularly workplaces. Furthermore, studies pay attention to distance-related fuel consumption, but ignore driver behavior and driving speed, and hence only partially reveal built environment effects on fuel consumption. Moreover, the majority of studies do not use actual fuel consumption in naturalistic driving, becoming vulnerable to measurement errors. This study applies a SEM to examine the impacts of the built environment at both residential and employment locations on actual fuel consumption of commute trips, through its influence on driving distance, driver behavior, and driving speed.

3. Methodology

3.1. Data and variables

This study chose Beijing as the city for empirical analysis. Beijing is a predominantly monocentric city with six road rings from the core to the city periphery. In Beijing, office buildings are likely to be concentrated in the inner rings, while residential development is likely to be distributed in the outer rings. According to the 2016 Beijing traffic development annual report issued by the Beijing Transport Institute, commuting accounted for 52% of all trips in 2015. Personal vehicles accounted for 31.9% of the commute mode choices, and bus, shuttle, rail transit, taxi, and bike accounted for 25.0%, 11.9%, 25.0%, 3.6%, and 12.4%, respectively. The share of auto commute in Beijing does not differ greatly from other large Chinese cities, which have a higher development density and a lower auto ownership than most cities in developed countries.

This study analyzed commute trips based on on-board diagnostics (OBD) data, provided by Beijing Yesway Information Technology Co., LTD. through a research-oriented agreement. The OBD data were obtained from a portable application, which records the operating status of vehicles at nine-second intervals. The fuel consumption monitoring of OBD devices realizes dynamic real-time quantification of fuel consumption. Based on the OBD data, we identify individual trips, trip routes, the location of trip origins and destinations, compute trip distance, average speed, total fuel consumption, and identify sudden speed changes such as hard acceleration and hard deceleration.[1] The OBD data include the information of 1483 private vehicles in Beijing during two months from July 1st to September 1st in 2015. Since this study focuses on morning commute trips, the number of vehicles reduces to 660. For each of the vehicles, one morning weekday commute trip during the two months was randomly selected for data analysis.[2] The origins and destinations of these 660 commute trips covered eight Beijing districts (Fig. 1).[3] The OBD data are anonymized and do not include demographic characteristics of drivers for confidentiality.

Five built environment variables are measured at both residential and workplace locations. Residential density, employment density, and road density are widely used in previous studies (Cao and Fan, 2012; Chen et al., 2008; Su, 2011). Distance to central business districts (CBD) is expected to affect commuting behavior (Ding et al., 2018; Hu et al., 2018). Liu and Shen (2011) suggested that public transportation should be taken into consideration in future studies on the relationship between urban form and fuel consumption. Thus, we also include distance to city center and access to metro station. In particular, this study extracted the distribution of residential buildings and office buildings from the point of interest (POI) data of Baidu, a popular search engine in China. We set up 500-m buffer zones for trip origins (home) and destinations (workplace) in ArcGIS, counted the numbers of residential and office buildings, and computed residential building density and employment building density, respectively. Using transportation network data of the Baidu POI, we calculated the density of roads within these buffer zones. We also created a dummy variable to indicate whether a metro station is available in these zones. Distance to city center was estimated based on the Euclidian distance from home (or workplace) to Tiananmen Square.

Furthermore, we computed proportion of expressways and proportion of secondary and minor roads to measure the street environment along the commute route, with major arterials being the reference category. These two variables capture the influence of

[1] A hard acceleration event means that accelerated speed is 2.22 m/s^2 or larger and the duration of acceleration is 2 s or longer. A hard deceleration event means that accelerated speed is -2.22 m/s^2 or smaller and the duration of deceleration is 2 s or longer. Therefore, these hard acceleration/deceleration events do not include common accelerations/decelerations during vehicle operation.

[2] Because our model controlled for the influence of the street environment along the commute route and individuals may choose different commute routes during the period, we chose a random commute trip instead of averaging the characteristics of all commute trips.

[3] The OBD data include latitude and longitude data of trips. We examined individuals' trip patterns over time and concluded that these origins and destinations are residential locations and employment locations, respectively.

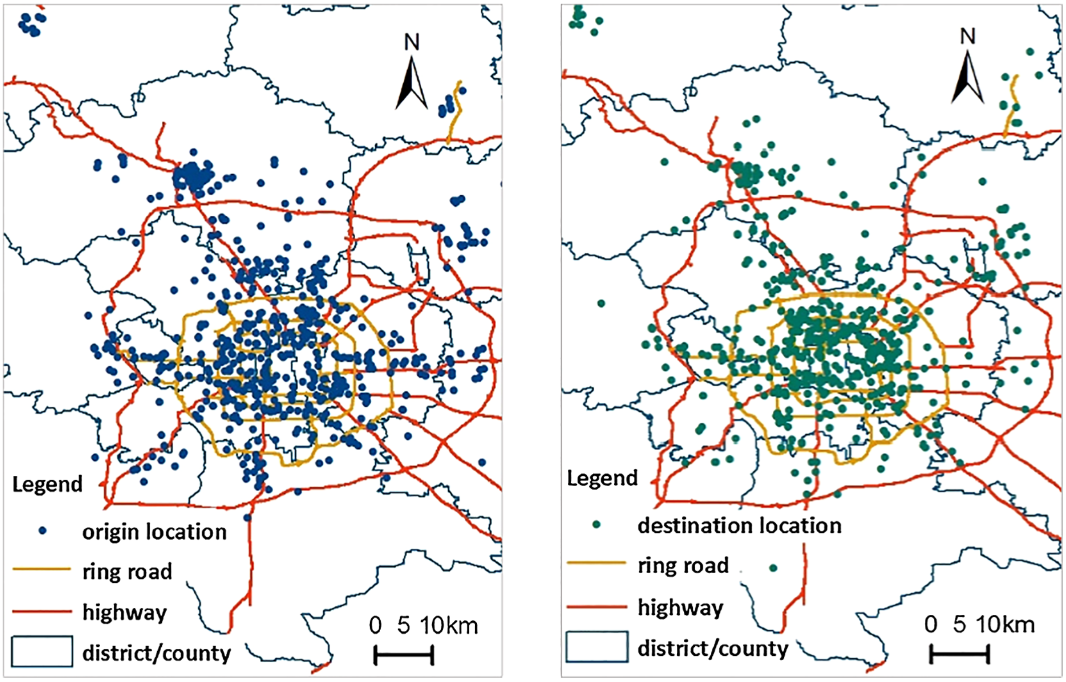

Fig. 1. Location distribution of commuting trip origins (the left figure) and destinations (the right figure).

commute route attributes on travel behavior and fuel consumption. They also serve as proxies for the built environment along the commuting route. Table 1 summarizes the variables used in this study and presents their descriptive statistics.

3.2. Conceptual framework and modeling approach

The literature suggests that the built environment affects fuel consumption directly and indirectly through intermediate factors (Fig. 2). In particular, we assume that the built environment of residential places as trip origins and workplaces as trip destinations

Table 1
Variable description and descriptive statistics.

Variables	Variable description	Mean	SD
Dependent variable			
Driving fuel consumption	Fuel consumption of the chosen commute trip in liter	1.48	0.96
Travel and driver behavior variables			
Acceleration events	Number of accelerations during the trip	0.42	1.27
Deceleration events	Number of decelerations during the trip	0.40	0.85
Commute distance	Trip distance (km)	15.58	11.33
Travel speed	Average driving speed of the trip (km/h)	27.86	10.14
Street environment variables			
Proportion of expressway	The proportion of which expressways account for the trip length	0.30	0.32
Proportion of secondary & minor road	The proportion of which secondary and minor roads account for the trip length	0.30	0.27
Residential built environment variables			
Distance to city center	The distance from the origin of the trip to Tiananmen Square (km)	18.30	13.81
Residential building density	Number of residential buildings per km^2 in the origin of the trip	155.65	119.64
Employment building density	Number of office buildings per km^2 in the origin of the trip	138.63	181.03
Availability of metro station	Whether metro stations are within walking distance in the origin of the trip (yes = 1, no = 0)	0.20	0.40
Road density	Length of roads per km^2 in the origin of the trip	11.77	5.13
Workplace built environment variables			
Distance to city center	The distance from the destination of the trip to Tiananmen Square (km)	16.64	13.72
Residential building density	Number of residential buildings per km^2 in the destination of the trip	180.03	153.45
Employment building density	Number of office buildings per km^2 in the destination of the trip	220.69	310.12
Availability of metro station	Whether metro stations are within walking distance in the origin of the trip (yes = 1, no = 0)	0.26	0.44
Road density	Length of roads per km^2 in the destination of the trip	16.10	6.39

Note: SD = standard deviation.

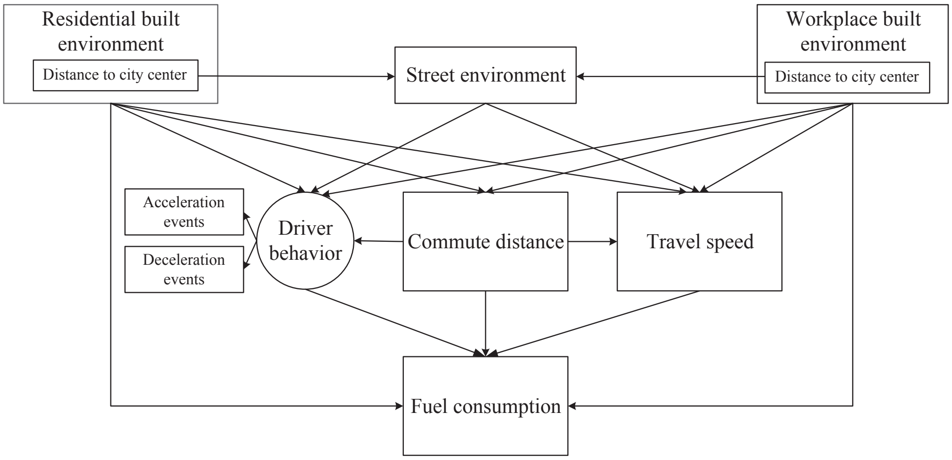

Fig. 2. The conceptual framework of travel fuel consumption.

influence commute distance (Ding et al., 2017a; Sun et al., 2017), travel speed (Liu and Shen, 2011; Wang et al., 2014), and driver behavior (Wang et al., 2014), which in turn affect fuel consumption. Furthermore, the built environment may have direct effects on fuel consumption, which represent those that are not captured by the intermediate variables. Commute distance is also expected to be associated with driver behavior and travel speed. Because of notorious traffic congestion during peak hours in Beijing, the number of acceleration events and deceleration events grows as commute distance increases. Commute distance is expected to be positively associated with travel speed (Ding et al., 2017a). Moreover, we assume that the street environment of the commute route affects driver behavior and travel speed.

The structural equations model approach is employed to estimate the relationships depicted in the conceptual framework. SEM is used widely in travel behavior research (Golob, 2003). It is an important statistical tool for multivariate analysis. It includes measurement models and/or path models. The former capture latent factors underlying a few related observed variables and the latter illustrate the causal paths among variables. In this study, driver behavior is a latent variable underlying two observed variables: acceleration events and deceleration events. All other variables are observed variables. Furthermore, SEM can capture direct effect, indirect effect, and total effect of a variable on the other. For example, the influence of the residential built environment on fuel consumption represents a direct effect, its influence though driver behavior is an indirect effect, and its total effect is the summation of the direct effect and all indirect effects.

4. Results

We adopted the robust maximum likelihood (MLR) method to estimate the SEM in *M*-plus because some variables do not follow the normal distribution. Table 2 presents goodness-of-fit indices of the final model, which are considered acceptable based on the cut-off values proposed by Byrne (2001). In the measurement model for the latent driver behavior, standardized coefficients for acceleration events and deceleration events are 0.427 and 0.581, respectively. Both factor loadings are significant at the 0.05 level and are more than 0.40, meeting the cut-off value recommended by Stevens (1996). Therefore, driver behavior is a valid latent variable for acceleration events and deceleration events. The rest of this section explains the path model.

Table 3 presents standardized direct effects, indirect effects, and total effects of the path model and Fig. 3 illustrates significant standardized direct effects. First, driver behavior, a latent construct for the frequency of sudden speed changes, is positively

Table 2
Model fit.

Model fit indexes	Description	Cut-off values	Model-based values
χ^2(df)	Evaluating the difference between observed and model estimated variance/covariance matrices. A smaller value indicates a better fit. However, χ^2 is highly sensitive to sample size, which means that the larger the sample size is, the bigger the value is.	$p > 0.05$	33.99 (33) $p = 0.42$
RMSEA	Measuring the amount of error of approximation per degree of freedom.	< 0.05	0.01
SRMR	Measuring the standardized average differences between the observed and estimated variance/covariance.	< 0.08	0.02
CFI	Assessing the improvement in non-centrality of setting model compared with the baseline model.	> 0.90	1.00
TLI	Assessing the improvement in lack of fit of setting model compared with the baseline model.	> 0.90	1.00

Note: RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual; CFI = Comparative fit index; TLI = Tucker Lewis index. The cut-off values for goodness-of-fit indices are based on Byrne (2001).

Table 3
Standardized coefficients of the structural equations model.

Variables	P1	P2	Driver behavior			Commute distance		Travel speed			Fuel consumption		
	Direct effect	Direct effect	Direct effect	Indirect effect	Total effect	Direct effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Driver behavior	—	—	—	—	—	—	—	—	—	—	0.159**	—	0.159**
Commute distance	—	—	0.313**	—	0.313**	—	—	0.601**	—	0.601**	0.974**	−0.074**	0.900**
Travel speed	—	—	—	—	—	—	—	—	—	—	−0.206**	—	−0.206**
Street environment													
Proportion of expressway (P1)	—	—	0.046	—	0.046	—	—	0.069*	—	0.069*	—	−0.007	−0.007
Proportion of secondary & minor road (P2)	—	—	−0.050	—	−0.050	—	—	−0.112**	—	−0.112**	—	0.015	0.015
Workplace built environment													
Distance to city center	−0.103	0.237**	−0.090	−0.123**	−0.213*	−0.341**	−0.341**	0.163**	−0.238**	−0.075	0.008	−0.350**	−0.343**
Residential building density	—	—	−0.087	−0.026**	−0.113*	−0.084**	−0.084**	−0.160**	−0.051**	−0.211**	0.028*	−0.057	−0.028
Employment building density	—	—	−0.003	0.002	−0.001	0.006	0.006	−0.090**	0.003	−0.087*	0.052**	0.023	0.075*
Availability of metro station	—	—	−0.028	0.005	−0.023	0.017	0.017	−0.030	0.010	−0.020	0.017	0.017	0.033
Road density	—	—	0.214*	−0.035**	0.179	−0.112**	−0.112**	0.008	−0.067**	−0.060	−0.094**	−0.069	−0.163**
Residential built environment													
Distance to city center	−0.154**	0.033	0.122	0.027	0.150	0.115	0.115	−0.076	0.055	−0.021	−0.080**	0.140	0.060
Residential building density	—	—	0.035	0.003	0.038	0.010	0.010	−0.020	0.006	−0.014	0.008	0.019	0.026
Employment building density	—	—	−0.080	−0.013	−0.093	−0.042	−0.042	0.007	−0.025	−0.018	−0.017	−0.052	−0.069*
Availability of metro station	—	—	−0.052	−0.013	−0.065	−0.042	−0.042	0.020	−0.025	−0.005	0.002	−0.050*	−0.048
Road density	—	—	−0.045	0.014	−0.031	0.044	0.044	−0.043	0.027	−0.016	0.065**	0.042	0.106**
R^2	0.059**	0.069**	0.181**			0.066**		0.530**			0.872**		

– indicates no effect.
** indicates 95% statistical significance.
* indicates 90% statistical significance.

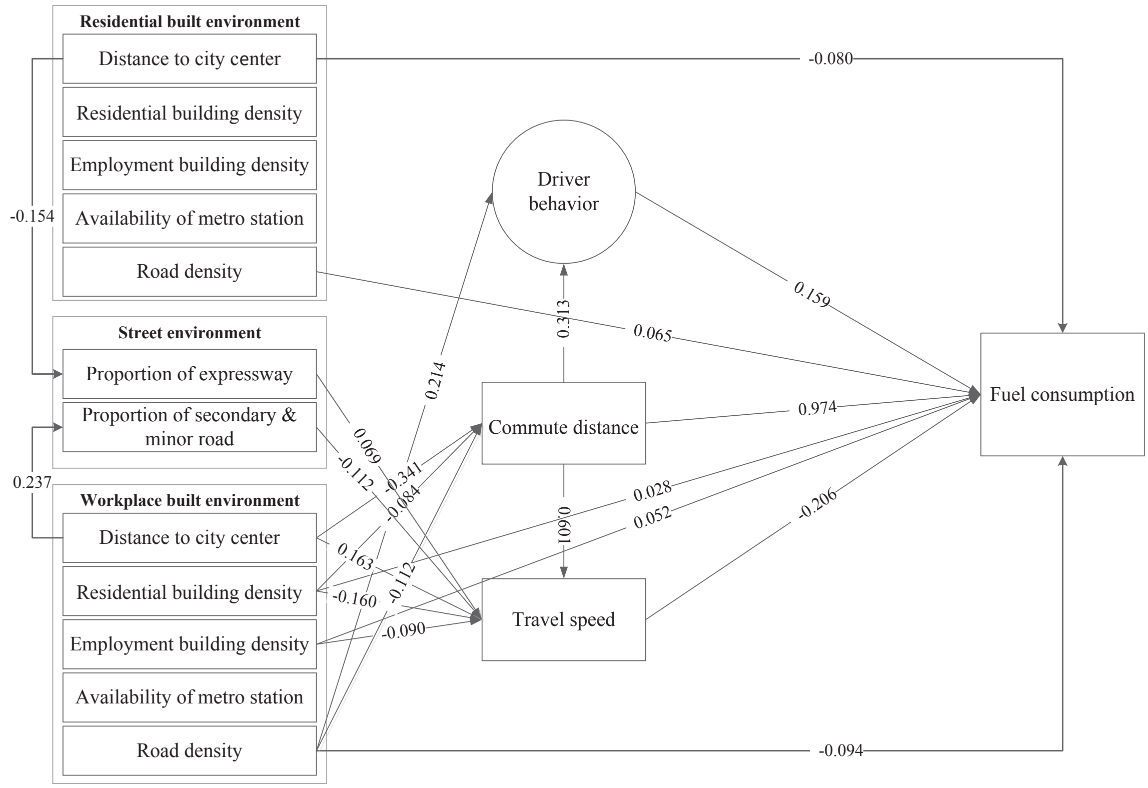

Fig. 3. Significant standardized direct effect coefficients.

associated with fuel consumption. This is reasonable as accelerations and decelerations reduce fuel efficiency, consistent with Wang et al. (2014). Second, average commute speed has a negative association with fuel consumption. Again, fuel efficiency of an average car reaches the maximum at about 88 kph (55mph). The negative association makes sense, because commute speed in Beijing is lower than 88 kph. This finding is also consistent with the literature (Liu and Shen, 2011; Wang et al., 2014). Third, the direct effect of commute distance on fuel consumption is positive, with a standardized coefficient of 0.974. Commute distance also has positive associations with travel speed and driver behavior, both of which are related to fuel consumption. The net indirect effect of commute distance on fuel usage is negative (−0.074) because the indirect effect through travel speed outweighs that through driver behavior. Accordingly, the total effect of commute distance is 0.900, which means that fuel consumption will increase by 0.9 standard deviations (SDs) if commute distance increases by one SD. Overall, commute distance influences fuel consumption through three channels—itself, driver behavior, and commute speed—and some of the channels work in opposite directions. A comparison of the standardized coefficients of commute distance, driver behavior, and travel speed suggests that commute distance plays a dominant role in fuel consumption.

The unstandardized coefficient of commute speed indicates that on average, an increase of 10 km per hour will reduce fuel consumption of a commute trip by 0.19 L (see Appendix Table A1). The unstandardized total effect shows that a commute distance of 10 km on average consumes 0.76 L of gasoline. Therefore, the effect of commute speed on fuel consumption is non-trivial. It is worth noting that driver behavior is a latent variable, we cannot quantify its influence on fuel usage directly.

The street environment along the commute route is significantly associated with travel speed: proportion of expressways has a positive correlation with travel speed whereas proportion of secondary and minor roads has a negative correlation, as expected. However, their effects on driver behavior and fuel consumption are insignificant. Distance from workplace to the city center has a positive association with proportion of secondary and minor roads. On the other hand, distance from home to the city center has a negative association with proportion of expressways. Their relationships are reasonable because in Beijing there are fewer secondary and minor roads in the inner rings than in the outer rings and there are more expressways in the inner rings than in the outer rings.

An overview of built environment variables shows that workplace locations has a larger impact on fuel consumption than residential locations. In particular, the total effect of distance from workplace to the city center is significant whereas distance from home to the city center is insignificant. Furthermore, the effect size of distance from workplace to the city center is the largest among all built environment variables in the model.

Among the five built environment variables at workplace locations, the total effects of distance to the city center, employment

building density, and road density are significant at either 0.05 or 0.1 level whereas residential building density and availability of metro station are insignificant. First, distance to the city center has a negative effect on fuel consumption. The negative effect is mainly through its indirect effect on commute distance and driver behavior. The farther the workplace is from the city center, the commute distance is shorter. This makes sense as the center attracts workers from all over the region and those working in the center tend to have a longer commute distance than others (Hu, 2015; Hu et al., 2018). Moreover, distance to the city center has a negative total effect on the frequencies of speed changes, particularly the indirect effect through commute distance. However, the total effect of distance to the city center on travel speed is insignificant because its negative indirect effect is largely canceled out by its positive direct effect.

Second, employment building density is positively associated with fuel consumption and the total effect is significant at the 0.1 level. As expected, a high employment density tends to reduce travel speed and, in turn, a lower speed increases fuel consumption. Its significant direct effect on fuel consumption implies that other influence mechanisms (for example, vehicle type choice) are also at work.

Third, the total effect of road density on fuel consumption is significantly negative. During peak hours, road density at workplace locations may influence fuel consumption in two different ways. A higher road density means a more reliable road network. Because multiple alternative routes to destinations are available, drivers have more choices to avoid traffic congestion. Therefore, a high road density reduces fuel consumption. This mechanism is congruent with the direct effect of road density on fuel consumption. On the other hand, a higher road density means a road network with more intersections. Traffic control at these interactions may require drivers to slow down or stop more frequently and reduce travel speed. Therefore, it may increase fuel consumption. The signs of the total effects of road density on travel speed and driver behavior are consistent with this mechanism, although neither are statistically significant. Surprisingly, road density has a significant and negative association with commute distance. Because the city center tends to have a higher road density and is associated with a longer commute distance, we expect a positive association between road density and commute distance. In a separate multiple regression (results not shown), we modelled commute distance as a function of distance from workplace to the city center and road density, and found that after controlling for the distance variable, road density does have a negative association with commute distance. This negative relationship is plausible because road density is an indicator of street connectivity and a higher road density tend to result in a shorter distance. Therefore, road density also helps reduce fuel consumption through its negative effect on commute distance.

Two measures of the residential built environment have significant total effects on fuel consumption and three measures are insignificant. Road density has a positive total effect on fuel consumption. The effect is mainly from its direct effect (significant) and the indirect effect through commute distance (insignificant). Overall, road density at residential locations and workplace locations have opposite influences on fuel consumption. Because we have considered the influence of road density on driving distance, driver behavior, and average driving speed, there is an unknown mechanism at work. Additional studies should be conducted to examine whether the significance is due to a type I error, and if not, identify what the mechanism is.

Furthermore, employment building density at residential locations has a negative total effect on energy consumption, which is not large and significant only at the 0.1 level. The effect of this variable implies that a higher employment density at residential locations is associated with better job-housing balance and hence reduces commute distance. Although neither the direct nor indirect effects are significant, their combination effects are marginally significant. The size of its coefficient suggests that the influence of employment density is relatively weak.

It is worth noting that residential building density at workplaces is significant and has negative total effects on drivers behavior, commute distance, and travel speed (two are significant at the 0.05 level and one is significant at the 0.1 level), respectively. However, its total effect on fuel consumption is canceled out by its direct effect and indirect effect through these mediating variables, and hence becomes insignificant. Overall, this study shows that residential density has an influence on commute distance, but has no significant effect on fuel consumption. The implication is that if we model only the influence of residential building density on commute distance and use commute distance to estimate fuel consumption, we will overstate the influence of residential density on fuel usage. This highlights the importance of including driver behavior and average speed in the model of fuel consumption.

Availability of metro stations at either end of the commute trip has no significant influences on fuel consumption. This result should be interpreted with caution, however. Many studies concluded that proximity to rail transit influences household car ownership (Ding et al., 2017b; Huang et al., 2016a) and commute mode choice (Cao and Schoner, 2014; Huang et al., 2016b). Therefore, metro development should affect fuel consumption of all commuters as a whole. However, the subjects analyzed in this study include only commuters who drive to work, metro stations become irrelevant to their commute trip.

5. Conclusions

Using real-time fuel consumption data, this study developed a structural equations model to illustrate the influence of the built environment on commute fuel usage. It considers five dimensions of the built environment at both residential and employment locations: residential density, employment density, road density, distance to city center, and access to metro stations. The major mediating variables between the built environment and fuel consumption include driving distance, trip speed, and driver behavior, such as speed change.

Commute distance, driver behavior, and commute speed are associated with vehicular fuel consumption for commute. Commute distance directly affects fuel usage, but also influences fuel consumption through its effect on driver behavior and commute speed. Among the three variables, commute distance has the largest influence on fuel consumption, but the effects of driver behavior and commute speed are not negligible. Therefore, reducing commute distance through land use policies such as job-house balancing and job-worker matching is the key to lower driving-related fuel usage. Minimizing the stop-and-go traffic situation and improving commute speed can further enhance fuel efficiency. On average, reducing commute distance by 1 km lowers fuel consumption by 0.076 L and improving commute speed by 1 km per hour reduces fuel consumption of a commute trip by 0.019 L.

The built environment at employment locations has a more important effect on fuel consumption than residential locations, particularly distance from workplace to city center. The distance variable is negatively associated with commute distance and the number of acceleration and deceleration events. Overall, it has a negative impact on fuel consumption. During the past few decades, most new residential developments occur at urban fringes where employment opportunities are limited. This development pattern worsens job-housing imbalance in Beijing (as well as other cities in China) and thence increases commute distance (TaNa et al., 2017). Therefore, improving job-housing balance by attracting new jobs to and/or decentralizing existing jobs to employment centers appears to be viable strategies to reduce commute distance and fuel consumption. The negative influence of employment density at residential places also implies the importance of job-housing balance. Moreover, because Beijing has an extensive metro network, it is desirable to place large employment centers around metro stations and facilitate transit-oriented development. This also helps reduce the burden of metro stations at the urban core, which are notoriously crowded during peak hours. By contrast, sprawling job decentralization will undermine the role of transit, which is an essential component of the transportation system in densely-developed cities in China. Furthermore, the sprawling job dispersion will create challenges to households with multiple workers with fewer cars. Beijing governments adopted the vehicle license quota program to control the growth of auto ownership. Many households own one or zero cars because of the program. Transit-oriented employment centers can make transit maintain its attractiveness to one or multiple workers in these households. This study also found that road density at workplaces is negatively associated with fuel consumption. Therefore, when designing employment centers, it is desirable to design small blocks to increase road density. The well-connected street network can help reduce traffic gridlock. Overall, small block employment centers around metro stations are the planning goal.

On the other hand, although residential density at job locations negatively affects commute distance, its influence on fuel consumption is insignificant because it lowers commute speed. This effect would not be observed if we use the single-equation modeling approach. We may overestimate its impact on fuel consumption if commute distance is treated as a proxy for fuel usage, a common approach used in previous studies.

Beijing is a densely-developed mega city. Its development patterns and transportation system do not differ greatly from mega cities in China such as S hanghai, Guangzhou, and Shenzhen and other mega cities in East Asia such as Hong Kong, Seoul, and Tokyo. Therefore, we are comfortable generalizing the results of this study to these cities. However, the results are not applicable to most cities in North America, where urban sprawl is prevalent and the automobile dominates the transportation system. On the other hand, because most studies used the data originating from developed countries, particular the US, this study offers new evidence on the relationship between the built environment and vehicular fuel consumption in a different urban setting.

This study also has a few limitations. First, fuel consumption is affected by vehicles, drivers, road, and weather conditions. We did not consider the effects of vehicles and weather conditions. Second, similar to other big data, the OBD data do not include demographic variables and hence we cannot control for their influences on location choice and travel choice. For example, because affluent people tend to work in the inner rings and purchase gas-guzzlers, income could be a confounding factor between workplace built environment attributes and driving-related fuel consumption. Third, although we included the built environment at trip origins and destinations in the model, we did not consider the influence of the built environment along the remaining commuting route on driver behavior and travel speed. We assumed that the former has a more important effect than the latter because the remaining route is chosen for through traffic. Alternatively, we considered the influences of the proportions of expressways, secondary and minor roads of the commuting route on driver behavior and travel speed. Whether these proportions are adequate proxies for the built environment along the commuting route merits empirical investigations in future studies.

Acknowledgements

This work is supported by the National Natural Science Foundation of China (U1564212, U1764265, and 61773040), and Young Elite Scientist Sponsorship Program by the China Association for Science and Technology (2017QNRC001).

Appendix A

Table A1
Unstandardized coefficients of the structural equations model.

Variables	P1	P2	Driver behavior			Commute distance		Travel speed			Fuel consumption		
	Direct effect	Direct effect	Direct effect	Indirect effect	Total effect	Direct effect	Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Driver behavior	—	—	—	—	—	—	—	—	—	—	0.284**	—	0.284**
Commute distance	—	—	0.015**	—	0.015**	—	—	0.540**	—	0.540**	0.083**	−0.006**	0.076**
Travel speed	—	—	—	—	—	—	—	—	—	—	−0.019**	—	−0.019**
Street environment													
Proportion of expressway (P1)	—	—	0.076	—	0.076	—	—	2.181*	—	2.181*	—	−0.021	−0.021
Proportion of secondary & minor road (P2)	—	—	−0.100	—	−0.100	—	—	−4.262**	—	−4.262**	—	0.055	0.055
Workplace built environment													
Distance to city center	−0.002	0.005**	−0.004	−0.005**	−0.008*	−0.283**	−0.283**	0.122**	−0.178**	−0.056	0.001	−0.025**	−0.024**
Residential building density	—	—	0.000	0.000*	0.000	−0.006**	−0.006**	−0.011**	−0.003**	−0.014**	0.000*	0.000	0.000
Employment building density	—	—	0.000	0.000	0.000	0.000	0.000	−0.003**	0.000	−0.003*	0.000**	0.000	0.000*
Availability of metro station			−0.035	0.006	−0.028	0.425	0.425	−0.700	0.230	−0.471	0.037	0.036	0.073
Road density	—	—	0.018*	−0.003**	0.015	−0.200**	−0.200**	0.012	−0.108**	−0.096	−0.014**	−0.010	−0.025**
Residential built environment													
Distance to city center	−0.004**	0.001	0.005	0.001	0.006	0.095	0.095	−0.056	0.041	−0.016	−0.006**	0.010	0.004
Residential building density	—	—	0.000	0.000	0.000	0.001	0.001	−0. 002	0.001	−0.001	0.000	0.000	0.000
Employment building density	—	—	0.000	0.000	0.000	−0.003	−0.003	0.000	−0.001	−0.001	0.000	0.000	0.000*
Availability of metro station	—	—	−0.071	−0.018	−0.088	−1.197	−1.197	0.510	−0.646	−0.136	0.004	−0.121*	−0.117
Road density	—	—	−0.005	0.001	−0.003	0.098	0.098	−0.085	0.053	−0.032	0.012**	0.008	0.020**
R^2	0.059**	0.069**	0.181**			0.066**		0.530**			0.872**		

– indicates no effect.
** indicates 95% statistical significance.
* indicates 90% statistical significance.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2019.01.013.

References

Aleklett, K., 2012. Peeking at Peak Oil. Springer-Verlag, New York.
Appleyard, B., 2012. Sustainable and healthy travel choices and the built environment. Transp. Res. Record: J. Transp. Res. Board 2303, 38–45.
Brownstone, D., Golob, T.F., 2009. The impact of residential density on vehicle usage and energy consumption. J. Urban Econ. 65, 91–98.
Brundell-Freij, K., Ericsson, E., 2005. Influence of street characteristics, driver category and car performance on urban driving patterns. Transp. Res. Part D: Transp. Environ. 10, 213–229.
Byrne, B.M., 2001. Structural Equation Modeling with AMOS: Basic Concepts, Applications, and Programming. Lawrence Erlbaum Associates, Mahwah, NJ.
Cao, X., Fan, Y., 2012. Exploring the influences of density on travel behavior using propensity score matching. Environ. Plan. B: Plan. Design 39, 459–470.
Cao, X., Schoner, J., 2014. The influence of light rail transit on transit use: an exploration of station area residents along the Hiawatha line in Minneapolis. Transp. Res. Part A: Policy Practice 59, 134–143.
Cao, X., Yang, W., 2017. Examining the effects of the built environment and residential self-selection on commuting trips and the related CO_2 emissions: an empirical study in Guangzhou, China. Transp. Res. D: Transp. Environ. 52B, 480–494.
Chen, C., Gong, H., Paaswell, R., 2008. Role of the built environment on mode choice decisions: additional evidence on the impact of density. Transportation 35, 285–299.
Ding, C., Cao, X., Næss, P., 2018. Applying gradient boosting decision trees to examine non-linear effects of the built environment on driving distance in Oslo. Transp. Res. Part A 110, 107–117.
Ding, C., Lin, Y., Liu, C., 2014. Exploring the influence of built environment on tour-based commuter mode choice: a cross-classified multilevel modeling approach. Transp. Res. Part D: Transp. Environ. 32, 230–238.
Ding, C., Liu, C., Zhang, Y., Yang, J., Wang, Y., 2017a. Investigating the impacts of built environment on vehicle miles traveled and energy consumption: differences between commuting and non-commuting trips. Cities 68, 25–36.
Ding, C., Wang, D., Liu, C., Zhang, Y., Yang, J., 2017b. Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. Transp. Res. Part A: Policy Pract. 100, 65–80.
Ewing, R., Cervero, R., 2010. Travel and the built environment – a meta-analysis. J. Am. Plan. Assoc. 76, 265–294.
Ewing, R., Hamidi, S., Nasar, J.L., 2015. Compactness versus Sprawl: a review of recent evidence from the United States. J. Plan. Literature 30, 413–432.
Golob, T.F., 2003. Structural equation modeling for travel behavior research. Transp. Res. Part B: Method. 37, 1–25.
Hu, L., 2015. Changing effects of job accessibility on employment and commute: a case study of Los Angeles. The Professional Geographer 67, 154–165.
Hu, L., Sun, T., Wang, L., 2018. Evolving urban spatial structure and commuting patterns: a case study of Beijing, China. Transp. Res. Part D: Transp. Environ. 59, 11–22.
Huang, X., Cao, X., Cao, J., 2016a. The association between transit access and auto ownership: evidence from Guangzhou, China. Transp. Plan. Technol. 39, 269–283.
Huang, X., Cao, X., Cao, X., Yin, J., 2016b. How does the propensity of living near rail transit moderate the influence of rail transit on transit trip frequency in Xi'an? J. Transp. Geogr. 54, 194–204.
Jiang, Y., Zegras, P.C., He, D., Mao, Q., 2015. Does energy follow form? The case of household travel in Jinan, China. Mitig. Adapt. Strat. Glob. Change 20, 701–718.
Lee, S., Lee, B., 2014. The influence of urban form on GHG emissions in the U.S. household sector. Energy Policy 68, 534–549.
Liu, C., Shen, Q., 2011. An empirical analysis of the influence of urban form on household travel and energy consumption. Comput. Environ. Urban Syst. 35, 347–357.
Maharjan, S., Tsurusaki, N., Divigalpitiya, P., 2018. Influencing mechanism analysis of urban form on travel energy consumption—Evidence from Fukuoka City, Japan. Urban Science 2.
Nelson, A.C., 2017. Compact development reduces VMT: evidence and application for planners—comment on "Does Compact Development Make People Drive Less?". J. Am. Plan. Assoc. 83, 36–41.
Statista, 2018. Oil consumption in China from 1998 to 2016.
Stevens, J., 1996. Applied multivariate statistics for the social sciences, 3rd ed. Lawrence Elbaum Associates, Mahwah, NJ.
Stevens, M.R., 2017. Does compact development make people drive less? J. Am. Planning Assoc. 83, 7–18.
Su, Q., 2011. The effect of population density, road network density, and congestion on household gasoline consumption in U.S. urban areas. Energy Econ. 33, 445–452.
Sun, B., Ermagun, A., Dan, B., 2017. Built environmental impacts on commuting mode choice and distance: evidence from Shanghai. Transp. Res. Part D: Transp. Environ. 52B, 441–453.
TaNa, Chai, Y., Zhang, Y., Sun, D., 2017. Understanding job-housing relationship and commuting pattern in Chinese cities: past, present and future. Transp. Res. Part D: Transp. Environ.
Tian, G., 2017. Travel and Built Environment: Evidence from 23 Diverse Regions of the United States. The University of Utah. The University of Utah.
Wang, D., Zhou, M., 2017. The built environment and travel behavior in urban China: a literature review. Transp. Res. Part D: Transp. Environ. 52, 574–585.
Wang, X., Liu, C., Kostyniuk, L., Shen, Q., Bao, S., 2014. The influence of street environments on fuel efficiency: insights from naturalistic driving. Int. J. Environ. Sci. Technol. 11, 2291–2306.
Xiao, Z., Lenzer, J.H.J., Chai, Y., 2017. Examining the uneven distribution of household travel carbon emissions within and across neighborhoods: the case of Beijing. J. Region. Sci. 57, 487–506.